International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 1-16

https://doi.org/10.70917/ijcisim-2025-0312
Article

Exploring the Optimization Methods of Color Matching in Visual Communication Design Combined with Graphic Algorithms

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Abstract: In order to solve the problems of inefficiency of traditional color matching methods in visual communication design, this paper proposes a computer-supported color extraction and matching technology. Based on the improved K-Means clustering algorithm to achieve color adaptive extraction, the integration of visual perception and similarity metrics to complete the color matching evaluation. A sample database is constructed and students majoring in visual communication are selected as the survey object. The performance level of the color adaptive extraction algorithm in this paper is evaluated by comparing the similarity results of the reconstructed image and the original image. Combined with the perceptual evaluation survey data, with the help of factor analysis to mine the subjects' perceptual demand for color matching scheme, the color matching optimization scheme is proposed. The traditional color matching optimization method is chosen as a comparison to examine the superiority of the proposed method. At 500 iterations, the fusion degree of this paper's method reaches 93.59%, which is much higher than the 56.78%, 70.86% and 78.31% of other traditional methods. The output signal-to-noise ratio is 26.18 dB, which is 36.28% higher than the PID method with the second best performance. Meanwhile, the output rate of color matching visual reconstruction of this paper's method is stable between 85% and 92% under different iterations, with a fluctuation of no more than 10%.

Keywords: visual communication design; color adaptive extraction; visual perception; similarity metric; color matching optimization

1. Introduction

Visual communication design can be traced back to the printing art of European countries in the middle of the 19th century, designers were inspired by the process of graphic design of printed materials, and kept exploring the further expansion and extension of graphic design, which gradually developed into an independent field and was promoted at the World Design Conference in 1960, which triggered the attention of countries all over the world [1-5]. As a comprehensive discipline, visual communication design involves countless elements, among which color plays an important role [6-7].

Color plays an important role in visual communication design, color elements are not only visual components, but also can convey the emotion of the design work, so that the audience resonates with the work, so as to convey the information of the design work more reasonably [8-11]. The significance of the use of color elements in visual communication design is mainly to express emotion, convey information, brand recognition and so on. Color is an expresser of emotion, and various colors can cause different emotional responses [12]. For example, red can convey passion, power and love; blue conveys calmness, tranquility and trust; through the use of different colors, designers can let the audience produce a specific emotional experience [13-14]. At the same time, color can help people identify and understand information [15]. For example, traffic signals use red, yellow, and green colors to indicate stop, ready, and proceed. In visual communication design, designers can also use color to emphasize key information and make the design work more memorable and recognizable [16-17]. In addition, color plays an important role in brand design and can be a brand's logo and identity [18]. Many brands have their own unique color schemes, such as Coca-Cola's red, IBM's blue, etc. These colors become the symbol of the brand, which can allow consumers to visually identify the brand [19-21].

And effective color matching is an important factor in the emotional transmission of visual communication design. In view of the important application of graphic algorithms in solving various graphic problems, such as image processing, 3D model rendering, computer vision, etc., by combining with graphic algorithms, designers can synthesize and optimize the color combinations, so as to improve the coordination and expressive power of visual communication design [22-26].

Visual communication design realizes visual communication through the combination of text, graphics, and color, and the reasonable matching of color plays an important role in improving the visual design effect, and in the optimization method of color matching, in addition to graphic algorithms, genetic algorithms, blockchain, and other methods and models are also able to realize the optimization of color matching and improve the visual communication design effect. Literature [27] examined the role of color in visual communication design and compared the emotional effects of different colors in, indicating that color helps to improve the attractiveness and unique emotional communication, and brings an immersive visual experience for the audience, while different colors can trigger different emotional responses. Literature [28] discusses the role of visual communication design based on color psychology on consumer support, trust and purchase intention based on consumer psychology theory, revealing that consumer behavior is an outward manifestation of consumer psychology, and visual communication design based on color psychology plays a positive guiding role. Literature [29] analyzes the significance and effectiveness of color application in visual communication design, and illustrates the application and effect of color in visual communication design through case studies, emphasizing that color directly affects the visual and communication effects of design. Literature [30] emphasizes the importance of color in visual communication design, whether in the fashion industry or the healthcare industry, in terms of facilitating communication, establishing brand identity, and arousing emotional resonance. Literature [31] designed a model for matching text and color of product packaging based on visual communication, and experiments show that the model has high pixel extraction accuracy, performs well in text and color matching, and has strong performance in practical application. Literature [32] emphasizes the necessity of optimizing brand color design based on the importance of color for visual communication design, and proposes the optimization method of genetic algorithm to verify its effectiveness in optimizing color matching scheme. Literature [33] pointed out the challenges faced by visual communication design and proposed the integration of visual communication design and color balance into multimedia image analysis to enhance the visual impact of the image, and the results showed that the visual effect score of the image by this method has been improved, which provides a new perspective for improving visual communication design. Literature [34] studied the color matching design method for product visual communication based on grey correlation analysis, which can achieve effective color matching, improve the color coordination of the product, and meet the user's preference. Literature [35] proposed a color matching optimization method for visual communication design based on blockchain, which not only enhances the image enhancement effect and color matching optimization, but also significantly improves the overall perception of visual communication design. Literature [36] optimized the color matching of marine landscape decorative patterns, aiming to effectively improve the design quality of marine landscape, and systematically described the whole process of color matching optimization, revealing that the method has obvious matching effect and improves the quality of marine landscape design.

This paper first details the characteristics of visual perception based on visual perception related research. Improve the K-Means clustering algorithm and propose a color adaptive extraction model. Design a comprehensive evaluation system to measure the model color extraction effect. Construct the minimum color difference model and transform it into similarity measure. Rely on the target palette to recolor the source image and calculate the structural similarity measure to measure the image content similarity. Adopt feature-level fusion method to fuse similarity metrics with SSIM metrics to achieve color matching evaluation. Self-constructed sample database to explore the effectiveness of color adaptive extraction algorithm through experiments. Extract the color values of primary and secondary monochrome samples of experimental images, and screen the perceptual evaluation adjective pairs. Invite 100 students majoring in visual communication at school as subjects, and get the color matching scheme based on factor analysis. Evaluate the optimization effect of this paper's method from the three dimensions of information fusion, visual reconstruction output rate and output signal-to-noise ratio.

2. Research on color matching optimization system based on graphic algorithm

With the rapid development of computer technology, it has caused a certain impact on the color matching of visual communication majors. Graphical algorithms have long become a potential resource with high value that can be utilized to provide new development opportunities for contemporary visual communication design. The purpose of this paper is to explore the specific application path of graphical algorithms in color matching optimization, and to propose the whole process of visual communication color matching optimization based on color perception characteristics.

2.1. Research on the Visual Perception Characteristics of Color

People can visually perceive information such as size, shape, color, texture material, etc., among which color occupies a very important position. From the visual point of view, the visual perception of color occurs in the visual process of interaction between the human eye and the human brain. From the design point of view, color is an important design element, which can not only express the design intention, but also bring people the corresponding emotion through visual perception. Color has the function of enriching people's emotions through certain ways, for example, it can cause changes in people's emotions through the way of association. Designers can use the design to arouse positive emotions through the reasonable combination of colors. The visual perception of color is an important factor that connects color and people's psychological world. Therefore, a good color scheme design should make good use of the visual perception characteristics of color, taking into account people's visual subjective preferences and the visual response that color brings to people. To address this situation, we sort out and analyze the visual perception characteristics of the human eye about color, which is used to guide the analysis and design of subsequent research.

(1) Visual salience. According to the visual saliency of people's visual perception, in the process of visual perception, people will pay special attention to the attributes of objective objects with distinctive features, and then allocate their attention to extract and analyze the information of these attributes. People's visual system is driven by external stimuli to complete the allocation of attention. For example,

warm-colored objects are the first to attract people's attention in the surrounding environment. In product design, designers can utilize this human allocation mechanism to design products that attract users' attention.

(2) The visual firstness of color. In the process of visual perception, there is a pre-attention processing stage, the mechanism of this stage is similar to the subconscious mind of human beings, which is a stage before the formation of consciousness of the visual system. Some studies have shown that among the properties of objective objects that can produce visual information, color contrast is one of the features that attracts the attention of the visual system of the human eye the most, and there are also related experiments that show that color is a basic feature of the pre-attentive stage. That is to say, when people observe external objective objects, their color properties are the first to reach the optic nerve and give stimulation, and the role of color in people's visual physiological characteristics is very important and has priority. We call people's visual properties as “the first color visual properties”.

(3) Color perception characteristics. Color is studied as a visual sense, and it has various perceptual properties, such as color association, color adaptation, and the contrast between color perceptual properties. The details are as follows:

1) Color association. Color synaesthesia refers to the process in which the sensation produced by one sense organ triggers the production of sensation in the same or another sense organ. Color can be associated with people's sense of hearing, taste, touch and so on through vision, thus forming the color association. For example, lower-pitched sounds can be associated with darker colors.

2) Color adaptation. If color as a visual stimulus acts on people's perceptual organs for a long time, people's ability to perceive that color will change. When people observe colored things, color accounts for 80% of the sensation, and shape and form account for 20%. With the increase of time, the proportion of color will decline, people will pay more attention to the shape and form, until each accounted for half and maintain such a state of perception. To address this phenomenon, color research scholars believe that the best time for color perception is 5-10 seconds, based on which it is proposed that in the study of color perception can be studied through the overall, comparative, short and other observation methods. Reasonable color selection and color matching in design can improve people's freshness to the product.

3) Color contrast. The phenomenon that the attributes of color such as brightness or hue are affected by the surrounding environment to form differences is called color contrast. Color contrast is the contrast of color perceptual attributes, of which the brightness contrast is the most significant effect, compared with the color contrast and purity contrast is more important and the degree of human perception is more obvious. The human eye perceives different colors differently, and there is also a sense of distance and expansion and contraction. For example, the warm color of red gives people a sense of vividness and liveliness, and there will also be a sense of forward movement, while blue and other cold colors give people a sense of tranquility and relaxation, but also has a strong stimulus to give people a sense of space back. For example, the purity of the color will affect people's perception of the location of the color, the brightness of the color will affect people's perception of the size of the situation. Reasonable use of color properties contrast to the space design, can significantly increase the spatial sense of the space.

4) Color imagery. Color can trigger a series of feelings and emotions in people's psychology. Color imagery is influenced by people's psychology under the influence of different color attributes to the formation of different feelings, is a kind of abstract meaning. Color imagery words are words describing people's feelings about color attributes, and people's color imagery words can be summarized and analyzed through the semantic difference method. The process of color imagery action is shown in Figure 1, that is, the process of people's color imagery formation, which is closely related to visual perception, and is based on the formation of visual perception of important color properties.

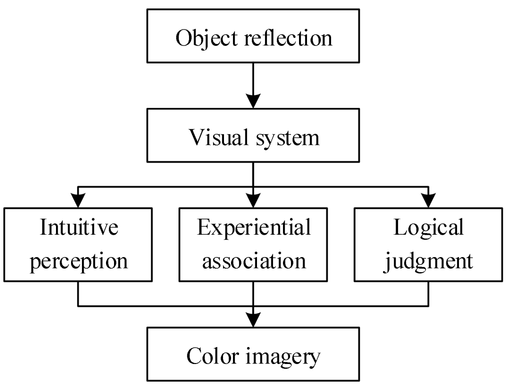

Figure 1. Color intention action process.

2.2. Color adaptive extraction model and evaluation system

Color extraction of images is the basis of intelligent color matching, and by identifying and analyzing the main colors in images or design samples with excellent color matching schemes, the visual effect of color matching can be improved and emotional expression enhanced. Traditional color extraction methods can only extract a fixed number of main colors in an image, which cannot effectively adapt to the complexity of the image, and the fixed number of extractions may lead to the merging or splitting of colors, which may produce color deviation and affect the final color matching effect. Therefore, this paper improves the K-Means clustering algorithm, which can only extract a fixed number of colors, and proposes a color adaptive extraction model. When using K-Means clustering algorithm for color extraction, its objective function is shown in equation (1).

$$M=\sum_{n=1}^{N}\sum_{k=1}^{K}r_{nk}C(n)-\mu_k^2 \tag{1}$$

In Equation (1), M represents the sum of the squares of the Euclidean distances from all pixels to their corresponding cluster centers, N represents the total number of sample colors, K represents the number of cluster centers, that is, the number of primary colors to be extracted, n represents the pixel index of the image, k represents the category of colors, and r_{nk} is a binary component. When the color of n pixels is of the k th class, its value is 1; otherwise, it is 0. $C(n)$ denotes the color of the n th pixel, and μ_k denotes the clustering center of the k th cluster, which is the average of the color values of all pixel points in the cluster. $\cdot$ denotes the Euclidean distance.The goal of the K-Means clustering algorithm is to minimize the objective function M by iteratively adjusting the clustering centers so that the sum of squares of the distances from each pixel point to its nearest clustering center is minimized. In image color extraction, the algorithm finds K color values that best represent the predominant colors in the image while making the sum of distances from all pixel points to their nearest color values minimum.

On this basis, the study uses the contour coefficient method to improve it, that is, by calculating the contour coefficient under different number of clusters, to find the number of clusters that maximizes the contour coefficient, and when the contour coefficient is the largest, the corresponding number of clusters is selected as the optimal number of colors. For each pixel p in the image, first calculate the distance between p and the center of the cluster it is located in, and then take the average of these distances to get the intra-cluster distance $a(p)$ of p, and second find the closest cluster center other than the one where p is located, and calculate the distance between p and the center of this cluster, and take the average of this distance as the inter-cluster distance $b(p)$ of p. Finally, the profile coefficient $s(p)$ is calculated as shown in equation (2).

$$s(p)=\frac{b(p)-a(p)}{\max(a(p),b(p))} \tag{2}$$

In Eq. (2), $\max(a(p),b(p))$ indicates taking the larger value of $a(p)$ and $b(p)$. After obtaining $s(p)$, the overall profile coefficient S of the clusters is calculated as shown in equation (3).

$$S=\frac{1}{L}\sum\nolimits_{p\in P}s(p) \tag{3}$$

In equation (3), L denotes the total number of pixel points, and P denotes the set of all pixel points. After completing the color extraction, there will be a color difference and so on, therefore, the study is based on the color adaptive extraction model, design a set of comprehensive evaluation system for measuring the model color extraction effect. After combining the extraction model with the comprehensive evaluation system, the process of color adaptive extraction is shown in Figure 2.

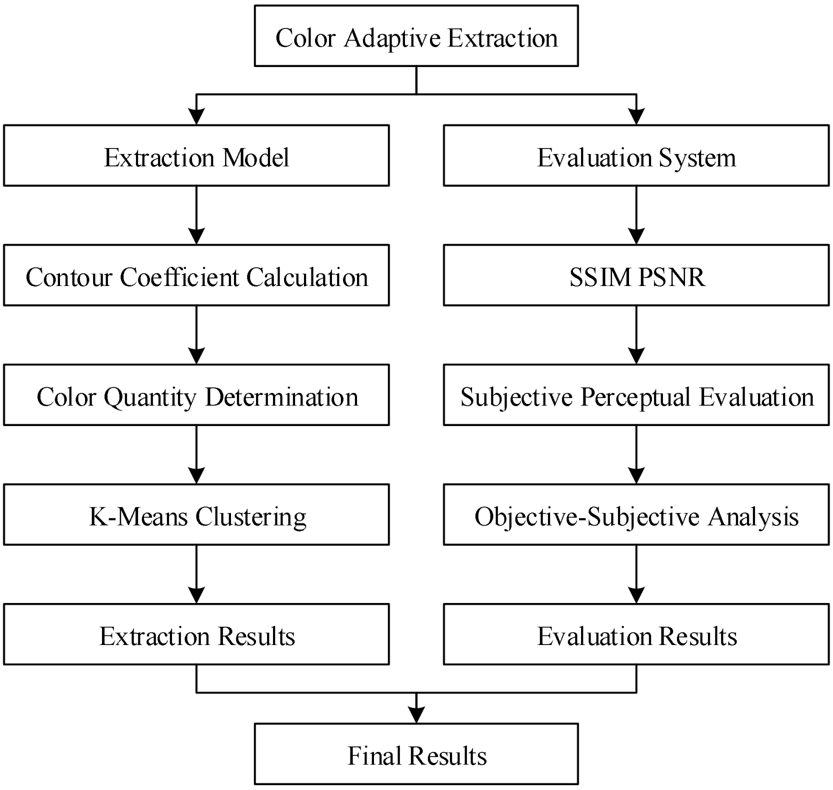

Figure 2. Comprehensive process of color adaptive extraction.

As can be seen from Figure 2, the comprehensive evaluation system involves both objective and subjective evaluations, in which the objective evaluation utilizes two metrics, structural similarity (SSIM) and peak signal-to-noise ratio (PSNR). The objective evaluation process is as follows: first, the original image is converted from the RGB color mode to the Lab color mode, which takes into account the perceptual uniformity of human vision and can provide a more consistent and predictable color comparison. Secondly, each pixel point of the image is examined one by one and the Lab color values of the examination results are recorded. Subsequently, the color difference between the Lab color value of each pixel point and all the extracted target colors is calculated, and the target primary color with the smallest color difference is selected to update the color value of that pixel point. Finally, a brand new image with extracted color replacement is generated and output, and the SSIM and PSNR between the original image and the brand new image are calculated.The objective evaluation metrics are shown in equation (4).

$$\begin{cases} A_1 = SSIM(I_o, I_1) \\ A_2 = PSNR(I_o, I_1) \end{cases} \tag{4}$$

In Eq. (4), A_1 and A_2 represent the metrics related to SSIM and PSNR, respectively, and I_o and I_1 represent the original image and the image filled with the extracted colors, respectively. The subjective evaluation in the comprehensive evaluation system relies on personal perception, experience and preference, which provides valuable user perspectives for color adaptive extraction.

2.3. Color matching evaluation integrating visual perception and similarity metrics

The color matching evaluation method fusing visual perception and similarity metrics constructed in this section is shown in Fig. 3, and its technology-specific implementation process is described below.

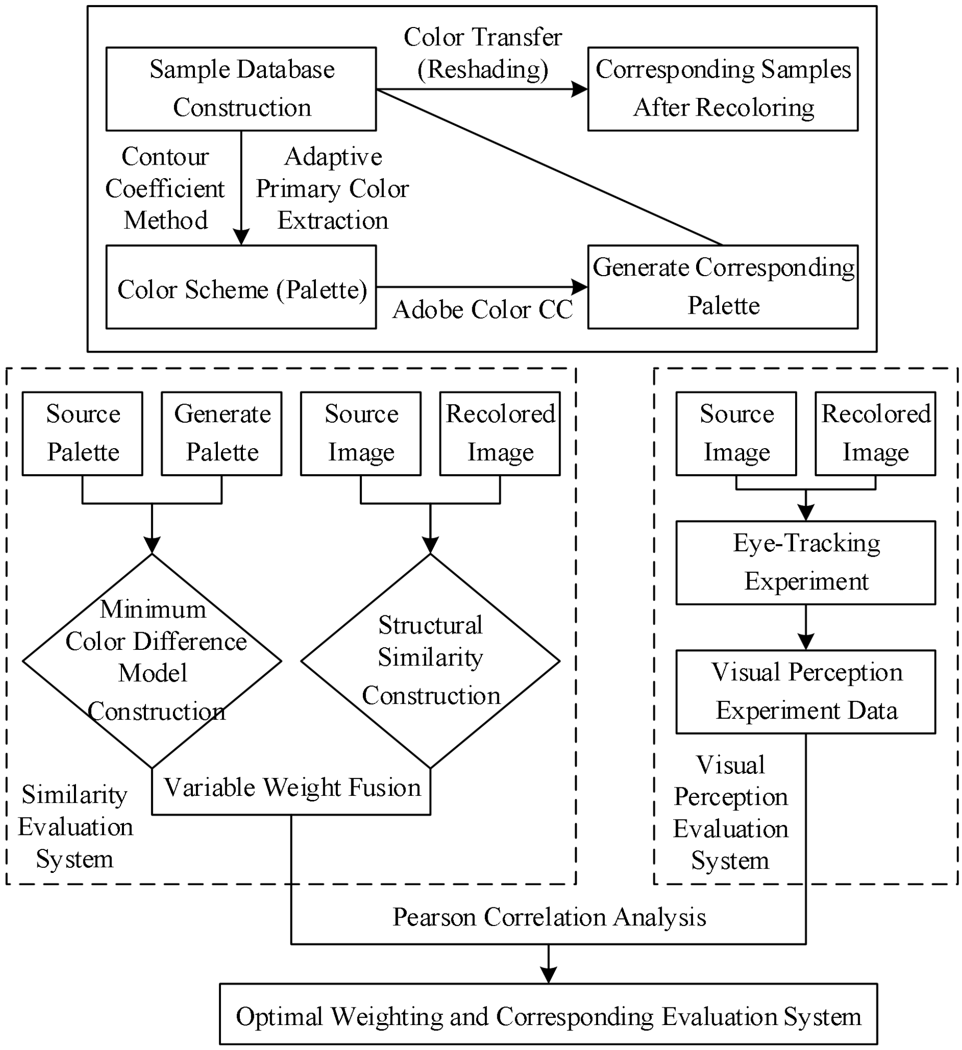

Figure 3. Technical process of color matching evaluation method.

2.3.1. Minimum color difference model and palette similarity measures

The traditional method of measuring the similarity of color matching schemes fails to take into account the different positions of each color block in the palette, which leads to the inaccurate calculation of the color difference between pairs of palettes. In order to scientifically and effectively describe the similarity between palettes made of multiple color combinations, the traditional method of calculating the color difference of palettes is improved, and a minimum color difference model combining position information is proposed. The method is to avoid the different calculation results due to the different positional information by introducing the strategy of intermediate palette for pairs of palettes, and the specific calculation methods are as follows:

Step 1: Assuming that the number of primary colors in both the source and target palettes is n, the source palette is denoted as palette P_1, iterate through all the colors in palette P_1 and compute the Lab values of all the colors in P_1; The target palette is denoted as palette P_2, and iterates through all the colors of the target palette P_2 and calculates the Lab values of all the colors of P_2.

Step 2: Calculate the color difference of the first color of the source palette P_1 using all the colors in the target palette P_2 respectively, record all the calculation results with their corresponding colors in P_2, and use the color block corresponding to the smallest value of the calculation results to place it as the first color of the intermediate palette, which is recorded as P_3.

Step 3: Cyclic operation is performed for the processing of Step 1 and Step 2, respectively, using all the colors of P_2 and then calculating the color difference of the remaining $n-1$ colors of P_1 one by one and determining the remaining colors of P_3 in the same manner as that in Step 1 to ultimately obtain the complete intermediate palette of P_3.

Step 4: Calculate the average color difference value between P_1 and P_3, which is calculated as defined below:

$$m_1 = \frac{\sum_{i=1}^{n} \Delta E_i}{n} \tag{5}$$

The color of the pair of palettes is the first color of the pair:
i - the i th color pair of the paired palette;
n - the total number of palette colors;
ΔE_i - the color difference corresponding to the i th pair of colors;
m_1 - the average color difference of the palette P_1 to P_3.

Step 5: Use the n colors of the source palette to obtain the color difference of all the colors of the target palette in turn and obtain a new intermediate auxiliary palette notated as P_4 in accordance with the processing method in Step 2, respectively.

Step 6: The average color difference between P_2 and P_4 is obtained by calculating using the method in Step 3 noted as m_2.

Step 7: The calculation method proposed in this section for evaluating the similarity of color palettes is defined as follows:

$$m = (m_1 + m_2)/2 \tag{6}$$

The computational steps of the minimum color difference model proposed in this section are shown in Fig. 4.

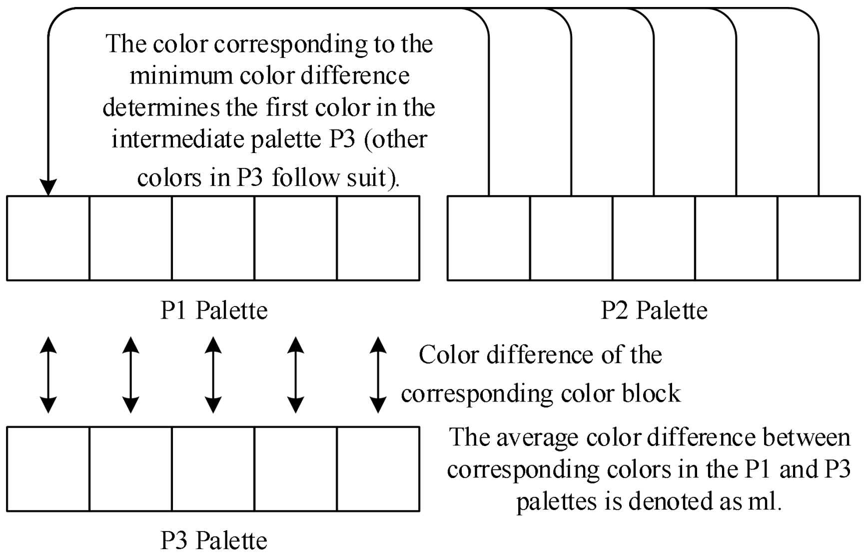

Figure 4. Calculation method of intermediate auxiliary palette P_3.

This section investigates the similarity of pairwise palettes, which requires the color difference results of pairwise palettes to be computationally processed to obtain the similarity based on the contents of the palettes. The calculated color difference results are normalized and the normalization method and the similarity calculation of the paired palettes are defined as follows:

$$M = \frac{m - m_{\min}}{m_{\max} - m_{\min}} \tag{7}$$

$$S = 1 - M \tag{8}$$

In the formula:

m , $m_{\min}$, $m_{\max}$ - represent the minimum color difference of the current paired palette, the minimum color difference among all palettes, and the maximum color difference, respectively;

M , S - the normalized result and the palette similarity measure.

2.3.2. Structural Similarity Measurement Based on Image Content

In the process of intelligent color matching, due to the strong applicability of the color matching scheme, it is often necessary to apply the matched palette scheme to the source image, and then further analyze the overall similarity measure from the perspective of image content. Therefore, in this section, based on the image recoloring technique, the target image is obtained by recoloring the source image using the target color palette, and the structural similarity between pairs of images is calculated under the evaluation dimension of image content in the following steps:

Step 1: Use the image recoloring technique to recolor the source image with reference to the image, and invite professional designers to screen the recolored target image, and eliminate images with obviously poor visual perception.

Step 2: Perform a structural similarity operation on the remaining target image and the source image corresponding to it, and calculate the SSIM metrics between the paired images.

2.3.3. Similarity Measurement Model Based on Feature Fusion

Since the above palette similarity measure and image content-based structural similarity measure represent the main color information and image content information respectively, which have relatively ideal independence, the feature-level fusion of them using variable weights is used to obtain the result based on the similarity calculation, and the method of feature fusion is defined in the following equation:

$$SIM = \left[\omega^* S + (1-\omega)^* SSIM \right] \times 100\% \tag{9}$$

Eq:

ω --variable weights;

S --Palette similarity measure;

$SSIM$ --Image similarity measure;

SIM --overall similarity measure.

3. Application analysis of color matching optimization in visual communication design

In this paper, the sample database is constructed by means of manual collection and crawler technology, etc. In order to ensure the scientificity and robustness of the samples, the constructed sample database is selected and categorized from the perspectives of image attributes and image styles. All the collected samples are screened, and only the samples with rich color information (the number of main colors is greater than or equal to 4) are retained. In total, a total of 100 experimental sample images were obtained.

3.1. Color Adaptive Extraction

In this section, the proposed color adaptive extraction algorithm is used to extract the feature colors of ten experimental sample images, and the corresponding color cards and reconstruction maps are drawn. In order to further confirm the effect of the algorithm feature color extraction and image reconstruction, PSNR and SSIM similarity quantification is carried out, and the similarity results between the reconstructed image and the original image of this paper's algorithm are shown in Table 1. For different images in doing the same feature color extraction reconstruction, the data metrics fluctuate with the color of the original image, the same image with the increase of the extracted feature color, the image reconstruction effect is getting better and better. For example, for the experimental image 1, when the extracted feature color is increased from 8 to 24, the PSNR is improved by 5.9764dB and the SSIM is improved by 13.04%.

Table 1. Similarity results.

Characteristic chromatic number	8 Characteristic colors		16 Characteristic colors		24 Characteristic colors	
Similarity index	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Image 1	24.3973	0.8018	28.9931	0.8937	30.3737	0.9322
Image 2	23.2862	0.7327	25.1172	0.8336	27.1736	0.8673
Image 3	25.3975	0.7663	28.0183	0.8664	29.4622	0.9115
Image 4	30.3762	0.9221	34.2864	0.9569	35.7631	0.9773
Image 5	26.0184	0.7462	28.1736	0.8455	30.0183	0.8836
Image 6	25.7538	0.7617	27.7737	0.8736	29.4861	0.9134
Image 7	21.0386	0.7893	22.2753	0.8551	24.8397	0.8896
Image 8	31.3863	0.9357	35.2266	0.9686	36.7738	0.9817
Image 9	24.7533	0.8183	29.0483	0.9018	31.3754	0.9442
Image 10	23.5864	0.7402	25.2268	0.8401	28.3862	0.8716

3.2. Color matching evaluation

The color values of primary and secondary monochrome samples in the sample image are shown in Table 2 and Table 3, respectively. The primary color monochrome samples are classified into 4 color families, and the secondary color monochrome samples have 12 kinds, and the secondary colors are selected according to the primary colors and color matching methods. From the perspective of hue, the monochrome samples were matched separately according to five color contrast methods: similar color, adjacent color, similar color, contrasting color and complementary color, and finally 18 stimulus maps were obtained.

Table 2. Primary color monochromatic sample color values.

Main color	Sample color	Hue	Purity	Brightness
Red-brown color range	Erythrosine	378	76	59
	Brick red	9	71	78
	Rose red	375	56	108
Orange-yellow color range	Coral zhu	12	68	104
	Apricot yellow	45	81	103
	Moonlit reflection	58	64	91
Blue-green color range	Green bamboo	80	41	54
	Lake green	172	49	81
	Plum green	84	21	79
	Deep blue	212	39	28
	Indigo	223	54	18
Purple color range	Violet	278	46	41
	Snowy blue	262	19	93
	Lilac color	298	16	85

Table 3. Auxiliary color monochromatic sample color values.

Sample color	Hue	Purity	Brightness
Deep navy blue	198	41	22
Spring blue	224	23	91

Blue gray	241	19	87
Greenish blue	203	88	62
Blue crane	192	41	78
Light mauve color	9	15	87
Beige	31	36	89
Withered and yellow	42	28	79
Branch yellow	28	31	94
Purple red	345	48	66
Autumn fragrance color	52	76	84
Moon white	31	22	94

Adjectives related to color psychology were collected and screened to obtain 25 pairs of perceptual evaluation adjective pairs. The collected word pairs were categorized based on the method of lexical categorization in Osgood's semantic difference method to remove similar adjective pairs. After expert guidance, 11 adjective pairs were modified and finalized. The online questionnaire was designed using the 5-level scale in the Likert scale, and 100 students majoring in visual communication in schools were invited as subjects, and the age of the subjects was between 18 and 26 years old. The subjects subjectively evaluated the 18 stimulus maps in the questionnaire based on their first impressions. "1" indicates that the emotional evaluation is very biased towards left-leaning adjectives, "2" indicates that the evaluation is relatively biased towards left-leaning adjectives, "3" indicates that the evaluation is neutral, "4" indicates that the evaluation is relatively biased towards right-leaning adjectives, and "5" indicates that the evaluation is very biased towards right-leaning adjectives. A total of 100 questionnaires were distributed, and 100 valid questionnaires were retrieved, with a recovery rate of 100%.

The factor analysis needs to be analyzed for the factor model to do adaptation before factor analysis. The KMO and Bartlett's Sphericity test was performed on the mean results using SPSS software, and the KMO value was tested to be 0.718, which is greater than 0.5, and the significant difference Sig value was 0.000, which is less than the significance level of 0.05, which indicates that the data are suitable for subsequent factor analysis. The total variance explained by adjective pairs is shown in Table 4. The eigenvalues of Component 1, Component 2, Component 3 & Component 4 are 4.685, 2.876, 1.206 and 1.004 respectively, because only the components with eigenvalues greater than 1 can be used as the principal components in principal component analysis, so 4 principal factors can be extracted from the 11 factors and the perceptual adjective pairs can be categorized into 4 groups.The cumulative variance contribution rate of the 4 principal factors is 88.738%, which is a significant contribution to the The loss of factor interpretation is less, so these 4 factors can summarize most of the information of the adjective pairs in the experiment, achieve the purpose of data dimensionality reduction, and be able to better interpret the subject's perceptual needs for color schemes.

Table 4. Total variance of the explanations for adjective pairs.

Component	Initial eigenvalue			Extract the sum of squares of the load values		
	Total	Variance percentage	Cumulative/%	Total	Variance percentage	Cumulative/%
1	4.685	42.548	42.548	4.685	42.548	42.548
2	2.876	26.119	68.667	2.876	26.119	68.667
3	1.206	10.953	79.620	1.206	10.953	79.620
4	1.004	9.118	88.738	1.004	9.118	88.738

5	0.491	4.459	93.197			
6	0.312	2.834	96.031			
7	0.195	1.771	97.802			
8	0.099	0.899	98.701			
9	0.078	0.708	99.409			
10	0.056	0.509	99.918			
11	0.009	0.082	100.000			

In order to determine the internal characteristics of the principal factors and explain the named factors, it is necessary to perform orthogonal rotation on the factor loading matrix. The maximum variance method was selected to rotate the factors. The rotation converged after 6 iterations, and the factor rotation matrix was obtained. The rotation component matrix is shown in Table 5. The larger the absolute value of the factor loading after rotation, the closer the relationship between the corresponding variable and the factor, and the greater the factor contribution. The four pairs of adjectives "warm - cold, friendly - distant, active - calm, monotonous - conspicuous" have a relatively large load on the first factor. The load of the "active - calm" variable at factor 2 reaches 0.542, but its contribution is relatively small compared to the 0.817 load of factor 1. So here, the adjectives "active - calm" are grouped together as factor 1. According to the meanings of these four variables, the first factor is named the "aura factor". The three pairs of adjectives "splendid - simple, individualistic - popular, reserved - flamboyant" have a relatively large load on the second factor. The second factor mainly explains the above three variables, so it is named the "personality factor". "Green - mature, light - heavy" has a relatively large load on the third factor, and the third factor is named the "formal factor". The two pairs of adjectives, "elegant - vulgar, retro - modern", have a relatively large load on the fourth factor, so the fourth factor is named the "harmonious factor".

As can be seen from the above, the subjects' perceptual evaluation of the design color scheme mainly includes four factors: "aura factor", "personality factor", "formality factor" and "harmony factor". Designers can, based on their emotional evaluation results, then design visual communication design color matching schemes that meet their needs.

Table 5. Rotational component matrix.

Adjective pair	Component			
	Factor 1	Factor 2	Factor 3	Factor 4
Warm-Cold	0.847	0.183	0.029	-0.012
Friendly-Alienating	0.882	0.061	0.397	0.023
Active-Calm	0.817	0.542	0.238	-0.056
Monotonous-striking	0.467	-0.123	-0.039	0.084
Gorgeous-Simple	0.318	0.902	-0.044	0.012
Individual-Popular	-0.051	0.896	0.152	-0.287
Implicit-Exposed	-0.281	-0.912	-0.053	0.295
Juvenile-Mature	0.208	0.021	0.956	0.071
Light-Heavy	0.482	0.113	0.784	0.235
Genteel-Vulgar	-0.031	-0.302	-0.101	0.842
Retro-Modern	0.099	0.124	-0.344	-0.801

3.3. Color matching optimization

3.3.1. Information fusion optimization

The method of this paper and the PID method, principal component method, wavelet decomposition method for comparison experiments, to get the experimental sample image color matching information fusion reconstruction results, the fusion degree of this paper's method and the traditional method fusion results are shown in Figure 5. When the iteration number is 500 times, the fusion degree of this paper's method reaches 93.59%, which is much higher than the 56.78%, 70.86% and 78.31% of other traditional methods, which effectively improves the fusion ability of the three-dimensional distribution of the color matching graphics.

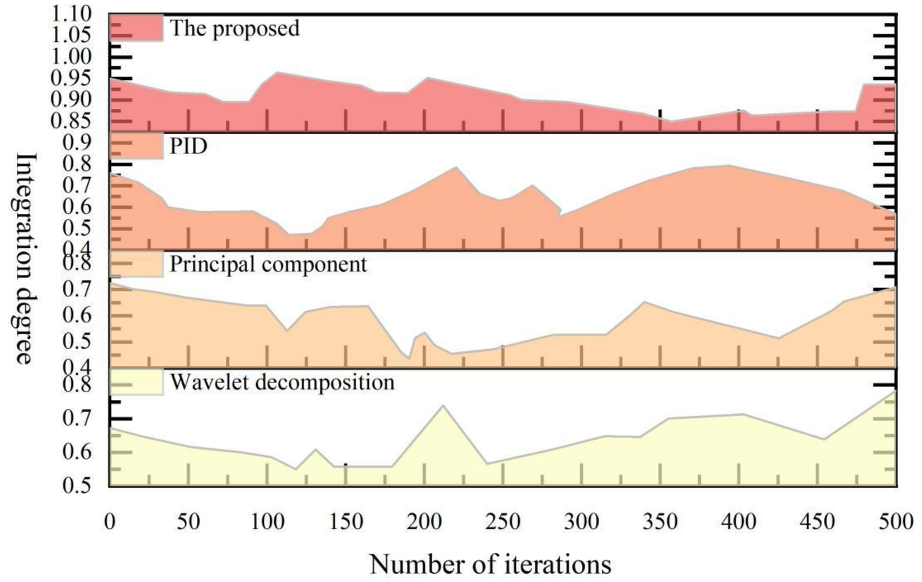

Figure 5. Comparison of color matching information fusion degree.

3.3.2. Color optimized output

Further to optimize the output of color matching images, the color matching output comparison between this paper's method and the traditional method is carried out, and the comparison results are shown in Fig. 6. The output rate of color matching visual reconstruction by this paper's method is stable between 85% and 92%, with a fluctuation of no more than 10%, and the output stability is good.

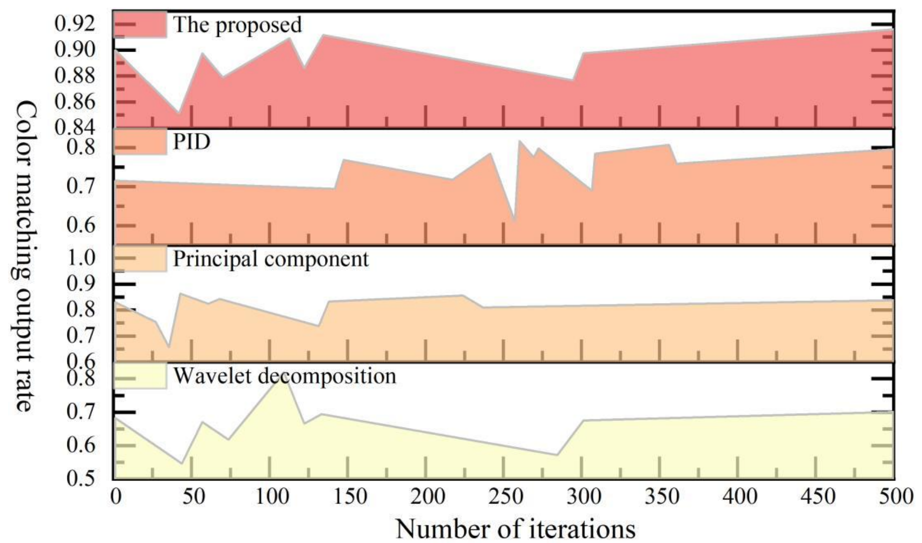

Figure 6. Color matching output comparison results.

3.3.3. Color Matching Signal-to-Noise Ratio Tests

The output signal-to-noise ratio of color matching is tested and the comparison results obtained are shown in Table 6. The output signal-to-noise ratio of color matching optimization by this paper's method is higher, and the output signal-to-noise ratio is 26.18 dB at the iteration number of 500, which is 36.28% higher than that of the PID method with the second best performance. It proves that the color matching optimization using the method of this paper can effectively improve the visual perception of the image.

Table 6. Output SNR comparison results(dB).

Number of iterations	The proposed	PID	Principal component	Wavelet decomposition
100	13.58	9.38	8.12	10.44
200	17.11	11.52	11.03	11.87
300	21.09	14.09	13.78	13.93
400	23.46	16.37	15.78	16.02
500	26.18	19.21	18.37	18.94

4. Conclusion

This paper constructs a color matching optimization system based on graph algorithm, and explores the applicability of the proposed method in the field of visual communication by designing experiments.

For different images when doing the same feature color extraction reconstruction, the data index fluctuates with the color of the original image, and the same image is reconstructed better and better with the increase of the extracted feature color. For example, for the experimental image 1, when the extracted feature color is increased from 8 to 24, the PSNR is improved by 5.9764 dB and the SSIM is improved by 13.04%.The cumulative variance contribution rate of the four principal factors reached 88.738%. The perceptual evaluation of the design color scheme by the subjects mainly includes four factors: "aura factor", "personality factor", "formal factor" and "harmony factor".

At 500 iterations, the fusion degree of this paper's method reaches 93.59%, which is much higher than the 56.78%, 70.86%, and 78.31% of other traditional methods, and effectively improves the fusion ability of the three-dimensional distribution of color matching graphics. The output rate of color matching visual reconstruction by this paper's method is stable between 85% and 92%, with fluctuations of no more than 10%, and the output stability is good. Meanwhile, the output signal-to-noise ratio of this paper's method is 26.18dB when the number of iterations is 500, which is 36.28% higher than that of the PID method with sub-optimal performance, which proves that this paper's method performs color matching with a better visual perception ability.

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